# Early retired or automatized? Evidence from the Survey of Health, Ageing and Retirement in Europe

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**Abstract**

This paper measures the implications of the actual destructive and transformative technological process in the labor market for the early retirement decisions in 26 European countries. In order to perform the analysis, we use the Survey of Health, Ageing and Retirement in Europe, the computerization probability (Frey and Osborne, 2017) and a technological classification of occupations in 4 occupational terrains (Fossen and Sorgner, 2019) to find that the current technological change is playing a significant role in the early retirement decisions, although it affect heterogeneously to certain groups in the sample (workers with higher education, self-employed workers and workers in occupations with low affectation by the technological change). This fact leads to a contradiction between governments trying to delay retirement ages and labor markets trying to expel workers earlier. Therefore, we conclude that, in order to elaborate policies on ageing and retirement, the effect of new technologies in older worker's decisions must be taken into account. We propose that the delay in statutory retirement ages should be accompanied by training programs and/or policies promoting self-employment for workers at risk of ending their working lives prematurely. Furthermore, the programs aimed to relocate middle-age workers displaced from their origin occupations should focus the finding of a destination occupation among those less impacted by new technologies (i.e., occupations in the human terrain).

**Keywords**: Early retirement, Technological change, Automation

**JEL Classifications**: H55 · J24 · J26 · O33

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## 1. Introduction

*New technologies* such as *Artificial Intelligence (AI) and Robotics* promise to bring profound changes to the *labor markets* in the coming years (Autor, 2015) and the current technological change is presumed to suppose a challenge for certain groups of population like *older workers* close to retirement age (Alcover *et al.,* 2021). Moreover, the ageing of the population in industrialized countries threatens the *sustainability of public finances,* in such a way that governments are extending the statutory retirement age (European Commission, 2021). This two facts – the automation process and the ageing of the population – lead to a *potential contradiction* between governments trying to extend statutory retirement ages and labor markets expelling older workers due to current technological changes.

On the one hand, in recent years, experts in AI have alert to the capacity of this new technology to assume tasks previously realized by humans.[1] At the same time, it has been analyzed the capacity of robotics to affect labor markets by reducing the employment rate (Acemoglu and Restrepo, 2020) and by increasing the productivity of workers (Graetz and Michales, 2018). However, although it has been proven that robots adoption reduces the employment rate, the implications of this employment rate reduction for the early retirement transitions have not been broadly studied.

On the other hand, the aged population of industrialized countries makes impossible to face the current industrial revolution with the same policies used during the previous ones. The concept of retirement as an old-age social insurance program appeared for the first time in 1889 designed by Otto von Bismarck, setting the retirement age at 70 years old. The life expectancy of the population in Germany then was around 40 years old, which made realizable this statement. Almost a century later, the early retirement provisions were adopted during the deindustrialization process between the late 1960s and 1970s and almost always immediately after the first severe decrease in industrial

[1] Grace *et al.* (2018) report the researchers' beliefs of AI outperforming humans in many activities in the next ten years, such as translating languages (by 2024), writing high-school essays (by 2026), driving a truck (by 2027), working in retail (by 2031), writing a bestselling book (by 2049), and working as a surgeon (by 2053). Their results from a large survey of machine learning researchers on their beliefs about progress in AI show that experts in AI believe there is a 50% chance of AI outperforming humans in all tasks in 45 years and of automating all human jobs in 120 years.

employment (Conde-Ruiz and Galasso, 2003). The life expectancy in the countries of the EU then was around 70 years old. Nowadays, with a life expectancy over 80 years old and the deepest technological change ever going on, the idea of incentivizing early retirement transitions for redundant middle-aged workers is out of the debate. In fact, governments are not only delaying statutory retirement ages but also stablishing more restrictive qualifying conditions, such as longer minimum contributory periods, stronger disincentives to retire, penalties for early retirement and bonuses for postponing retirement (European Commission, 2021).

Then, what are the solutions for the middle-aged workers seeking for continuing their working lives after being displaced by new technologies? In order to elaborate the proper policies on ageing, we find crucial to measure the impact of new technologies in the early retirement decisions. This paper contributes to the literature by analyzing the implications of automation process for the early retirement transitions in 26 European countries. In order to perform our analysis, we consider microdata from the Survey on Health, Ageing and Retirement in Europe (SHARE) and the probability of computerization provided by Frey and Osborne (2017). Furthermore, we use the measure of AI transformative effect by occupation provided by Felten et al. (2018) to extend the analysis by applying the classification of occupational terrains stablished by Fossen and Sorgner (2019).[2]

We find that the effect of automation in early retirement decisions has important implications for the creation of public policies on ageing and retirement. Specifically, we find differentiated effects in terms of education and job status, indicating that policies pursuing the working lives enlargement of the middle-aged workers should be focus on training programs and self-employment benefits and incentives for this collective. These training programs and self-employment incentives should be designed to guide the labor

[2] Fossen and Sorgner (2019) divide the occupational spectrum in 4 areas depending on the impact of transformative digitalization (Advances in AI) and destructive digitalization (automation). The area of occupations with low digitalization impact in both streams (transformative and destructive) is called the human terrain while the area of occupations with high digitalization impact in both streams is the machine terrain. The set of occupations with low automation and high advances in AI is the area of the rising stars occupations. Finally, occupations with low advances in AI and high destructive effect of digitalization are the collapsing occupations.

reintegration of these workers to populate the occupations at the lowest automation probabilities.

The rest of the paper is organized as follows. Section 2 presents a brief literature review on the impact of automation in the labor market and the determinants of the early retirement transitions. Section 3 collects the data used in the analysis. Section 4 details the modelling approach. Section 5 shows results. Finally, section 6 summarizes the conclusions derived from this research.

## 2. Literature review

This section presents a brief literature review in three levels. First, we consider some relevant works on the impact of automation in the labor market. Second, we examine some other noteworthy articles from the extensive literature on the determinants of early retirement. Finally, we reveal certain works in the intersection of this two strands of the literature, where this work fits.

### 2.1. The impact of automation in the labor market

Recently, many research works have been disseminated in order to clarify current automation processes. One of the main approaches in this analysis of the impact of new technologies on labor markets is that of the potential automation of tasks. In this line, Manyika *et al.* (2017) analyze more than 2,000 work activities across 800 occupations to find that about half of all the activities people are paid to do in the world's workforce could potentially be automated by adapting currently demonstrated technologies. They conclude that, while less than 5 percent of all occupations can be automated entirely using demonstrated technologies, about 60 percent of all occupations have at least 30 percent of constituent activities that could be automated.

Following this approach of tasks automation, at the next level of aggregation, we find out the discussion of potential occupations automation. Interpreting the definition of occupation as a set of tasks, calculating the automation potential of each task that makes up an occupation, we obtain data on the automation potential of concrete occupations. By applying this reasoning, Frey and Osborne (2017) assign a probability of computerization to 702 occupations using the SOC-2010 classification of occupations. In this broadly cited paper, the authors affirm that 47% of all US employment is at high risk of automation. Later, these results have been revisited by other researchers offering different visions of the automation process and incorporating other probabilities of computerization to the discussion.[3]

Fossen and Sorgner (2019) investigate the impact of new digital technologies upon occupations arguing that these effects may be both destructive and transformative depending of the destructive repercussions of digitalization (substitution of human labor) and the transformative consequences of digitalization (complementation of human labor). They distinguish between four broad groups of occupations that differ with regard to the impact of digitalization upon them: (i) *Rising star* occupations, characterized by the low destructive and high transformative effects of digitalization, (ii) *Collapsing* occupations, with high risk of destructive effects, (iii) *Human terrain* occupations, with low risks of both destructive and transformative digitalization, and (iv) *Machine terrain* occupations, affected by both types of effects.

Another approach to analyzing the effect of automation on the labor market has been to use data on robot adoption by industry. Acemoglu and Restrepo (2020) analyze the effect of the increase in industrial robot usage between 1990 and 2007 on US local labor markets, by using a model in which robots compete against human labor in the production of different tasks, to find that one more robot per thousand workers reduces the employment to population ratio by about 0.18-0.34 percentage points and wages by 0.25-0.5 percent. Also following this approach, Graetz and Michaels (2018) analyze the economic contributions of modern industrial robots, by using panel data on robot adoption within industries in 17 countries from 1993-2007 and instrumental variables that rely on robots' comparative advantage in specific tasks. They find that increased robot use contributed approximately 0.36 percentage points to annual labor productivity growth, at the same time it raises total factor productivity and reduces output prices. Contrary to the research of Acemoglu and Restrepo (2020), they argue that robots did not significantly decrease total employment, although they did reduce low-skilled workers' employment share.

To summarize the main nowadays challenges for this strand of literature, we highlight the three main sources of uncertainty about the macroeconomic implications of the

[3] For example, other authors claim that a same task may have different implications in different occupations. In this line, Arntz et al. (2016, 2017) repeated the analysis of Frey and Osborne (2017) setting the focus on tasks rather than in occupations to conclude that only 9% of the US occupations have high risk of automation.

technological change (Jimeno, 2019): the degree to which new machines and human labor will be complements or substitutes in the production of existing tasks embedded in the production of goods and services, the speed to which tasks performed by human labor could be automated, and the rate at which new tasks are created. Then, the new technological changes (robots, artificial intelligence, automation) may increase productivity growth but at the risk of having disruptive effects on employment and wages.

### 2.2.The determinants of early retirement decision

The early retirement decision is a topic that has been widely covered in the literature. Among the main determinants of the decision have always been personal circumstances such as financial situation and health or macroeconomic situations such as the political regime in which an individual lives or the generosity of the social security system.[4]

Regarding the implications of political regimes for the early retirement transitions, Bauman and Madero-Cabib (2021) find that early retirement is more frequent in social-democratic regimes (Denmark and Sweden) than in liberal welfare regimes (Chile and United States). In addition, they find that adverse health conditions are more frequent among early retirees in liberal but not in social-democratic regimes.

Regarding the influence of personal characteristics of an individual into the early retirement decision, Hernoes *et al.* (2000) find that financial incentives, educational background and industry affiliation influence retirement behavior. By applying a broader approach, Wilson *et al.* (2020) identify seven early retirement factors: health, good health, workplace issues, the work itself, ageism, social norms and having achieved personal financial or pension requirement criteria. Then, they propose six solutions to enable the enlargement of working life: occupational health programs, workplace enhancements, work adjustments, addressing ageism, changing social norms and pension changes.

Furthermore, early retirement literature has analyzed in detail the implications for early retirement of concrete policies. In this line, Schils (2008) finds that pursuing a shift from public to private early retirement schemes can lower the incidence of early retirement and, at the same time, the policy can make early retirement more selective in that only the higher paid are able to afford it. Besides, Hermansen (2015) shows that

[4] About the generosity of early retirement provisions, Conde-Ruiz and Galasso (2003) show, in a descriptive analysis of eleven OECD countries, that early retirement provisions were adopted during the deindustrialization process.

working in a company that offers reduced working hours for older workers does not have an effect on the relative risk of a 61- or 62-year-old withdrawing a full contractual pension in the next two years of their employment.

The SHARE – used in this study – has been broadly applied to the analysis of early retirement transitions. By using this survey, Siegrist *et al.* (2007) find a consistent association of a poor psychosocial quality of work with intended early retirement among older employees across all European countries and highlight the necessity for improved investments into better quality of work, in particular increased control and an appropriate balance between efforts spent and rewards received at work. Markova and Tosheva (2020) choose Bulgaria as the setting to analyze the determinants of an early exit from the labor market, finding that the early retirement plans are significantly shaped by gender and late career Bulgarians with a primary education are more likely to opt for early retirement than to look for low-quality jobs or be unemployed. Angelini *et al.* (2009) use the SHARE to describe an "early retirement trap" in which the interaction between early retirement and a limited use of financial markets produces financial hardship late in life. Hochman and Lewin-Epstein (2013) find that grandparenthood increases an individual's chances of looking forward to retiring early. This decision would not be forced by the need to care for their grandchildren since the effect observed is stronger in those countries that provide extensive childcare support.[5] Schmidthuber *et al.* (2021) use the SHARE to investigate how labour market and pension measures associated with active ageing influence retirement behaviour in Austria and Germany. Furthermore, we can find studies stablishing a connection of retirement with a healthy diet (Celidoni *et al.*, 2020), social relationships (Comi *et al.*, 2020), or self-employment (Axelrad and Tur-Sinai, 2021).

### 2.3.Considering automation as a determinant of the early retirement decision

We can find the consideration of automation as a possible cause of early retirement in documents from the 60s. In Barfield and Morgan (1969) we can read "…having experienced a change in the nature of one's job (for example, automation or other technological change) seems associated with having retired or planning to retire early".

[5] In this line, Van Bavel and De Winter (2013), using the European Social Survey, find that becoming a grandparent speeds up retirement, especially at the round ages of 55 and 60 years.

In this line, Bazzoli (1985) considered that economic variables play a more relevant role than health in retirement decisions.

More recently, Dorn and Sousa-Poza (2005) wonder if early retirement is a free or forced decision to conclude that, although the early retirement decision is usually explained as a supply-side phenomenon, it can also be a demand-side phenomenon arising from the firm's profit maximization behavior. These authors give special relevance to the distinction between 'voluntary' and 'involuntary' early retirement, finding the latter particularly widespread in Continental Europe (Dorn and Sousa-Poza, 2010).

Ahituv and Zeira (2011) combine the concepts of early retirement and technical progress to find that technical progress has two opposite correlations with early retirement: while it has a negative effect on labour supply of older workers, it raises wages on average and thus increases the incentive to remain at work.

Finally, an exception for the lack of evidence connecting the process of automation with the early retirement transitions would be the work developed by Yashiro et al. (2021), who measure this connection for the case of Finland by using the automation probability provided by Nedelkoska and Quintini (2018).

## 3. Data

Our analysis relies upon 3 levels and 5 data sources, as it is detailed below. In the first data level, we use microdata from the Survey on Health, Ageing and Retirement in Europe (SHARE) as a baseline to add the other two levels of data. In the second level, we have data linking occupations with the destructive and transformative effect of new technologies from two sources: (i) Frey and Osborne (2017) for the probability of computerization and (ii) Fossen and Sorgner (2019) for the classification of occupational terrains. Finally, in the third level, we have macroeconomic data to control by country for the economic situation (real GDP growth rate, from the World Bank; and harmonized unemployment rate, from Eurostat) and the generosity of social security system (old-aged pensions in PPS per inhabitant, Eurostat). This information about data level and sources is summarized in Table 1.

**Table 1**: Data levels and sources

| Data level | Data source |
|---|---|
| **Microdata** | SHARE (Eurofound) |
| Early retirement decision, gender, age, cohabiting status, health, financial situation, education, job characteristics | |
| | |
| **Measures for technological change by occupation** | |
| Probability of computerization | Frey and Osborne (2017) |
| The future of occupations | Fossen and Sorgner (2019) |
| | |
| **Macroeconomic data by country** | |
| Real GDP growth rate | World Bank |
| Harmonized unemployment rate and old-aged pensions in PPS per inhabitant | Eurostat |

The SHARE is a research infrastructure carried out from 2004 until today, accounting for 480,000 in-depth interviews with 140,000 people aged 50 or older from 28 European countries and Israel. In fact, SHARE is the largest pan-European social science panel study providing internationally comparable longitudinal micro data which allow insights in the fields of public health and socio-economic living conditions of European individuals. From 2004, SHARE has released 8 waves (with the third wave specialized in health and the eighth wave consisting in a COVID-19 survey). In our case, we live aside this special waves 3 and 8.

In particular, this paper uses data from the generated Job Episodes Panel.[6] Then, we merge some extra information of respondents from waves 1, 2, 4, 5, 6 and 7. In order to develop our work, it has been particularly important the information provided in the retrospective modules of wave 7, since they contain information about all working lives of respondents with high degree of detail. Within these modules, we can find the 2008 International Standard Classification of Occupations (ISCO-2008) 4-digits code for all occupations that respondents realized in their working lives. Therefore, these modules result crucial to merge the technological measures of automation probability and the transformative effect of AI.

After merging all the information required for our analysis into a single database, we finally stick with 26 European countries, as 3 of the countries in the SHARE (Israel,

[6] DOI: 10.6103/SHARE.jep.710. See Brugiavini *et al.* (2019) and Antonova *et al.* (2014) for methodological details.

Ireland and The Netherlands) are lost because of unavailability of data (for example, we do not have a disaggregation at 4-digit level for occupations in Ireland). Then, our geographical coverage is the following: Austria, Germany, Sweden, Spain, Italy, France, Denmark, Greece, Switzerland, Belgium, Czech Republic, Poland, Luxembourg, Hungary, Portugal, Slovenia, Estonia, Croatia, Lithuania, Bulgaria, Cyprus, Finland, Latvia, Malta, Romania, Slovakia.

The job episodes panel and the retrospective information contained in the different waves allow us to follow the individuals for their entire life since birth. However, for assuring representativeness of our results and given that we are trying to measure the impact of the current technological change in the early retirement decisions, we restrict our sample so that (i) the time coverage spans 14 years from 2004 to 2017 and (ii) individuals are over 50, the age from which individuals are eligible to be interviewed at SHARE.

Then, the sample is composed by men and women over 50 younger than their statutory retirement age who are workers (employees, civil servants or self-employed workers) in period *t* and either (i) become early retirees in period *t*+1 ($WO_t \rightarrow ER_{t+1}$) or (ii) remain as workers in period *t*+1 ($WO_t \rightarrow WO_{t+1}$). Finally, our sample is composed of 121,026 observations, corresponding to 17,551 individuals. In this sample, we find 6,408 transitions from work to early retirement.

## 4. Modelling approach

Our *dependent variable* (early retirement) takes value of 1 when a worker decides to retire before his retirement age and 0 when the individual remain working. Thus, given the binary nature of our dependent variable we estimate the probability of early retirement using *logit* models and report *average marginal effects*.[7]

As we aforementioned, the *main explicative variables* are the *automation probability* (Frey and Osborne, 2017) and the technological *classification of occupational terrains* (Fossen and Sorgner, 2019). The automation probability variable categorise occupations according to their susceptibility to computerisation, based on advances in

[7] Our results are robust to several specifications of the variance covariance matrix corresponding to the parameter estimates. In addition, we also check if panel-level variance component is important, but the likelihood-ratio tests performed point for the use of the pooled estimator.

Machine Learning and Mobile Robotics (Frey and Osborne, 2017). In our analysis, this variable is included first as a continuous variable, so that we estimate how the probability of early retirement change when the automation probability increase in one percentage point. From this variable we construct a dummy variable that takes value 1 when the automation probability is higher than 70% (high automation risk variable).

In order to consider not only the destructive impact of new digital technologies upon occupations, but also the transformative effect of digitalization on occupations, we also consider in our analysis the classification for the future of occupations by Fossen and Sorgner (2019). Thus, by combining information on automation probability by Frey and Osborne (2017) and a measure for AI transformative effect provided by Felten et al. (2018), the proposed classification includes four different types of occupations, as summarized in Table 2.[8] Thus, depending on their affectation by AI or automation, occupations can be classified in four different categories: (i*) human terrain* are occupations with low effect of AI advances and low automation risk, (ii) *rising stars* are occupations with high effect of AI advances and low automation risk, (iii) *collapsing occupations* are those with low effect of AI advances and high automation risk and (iv) *machine terrain* are occupations with high effect of AI advances and high automation risk. Therefore, the variable for the classification for the future of occupations takes values from 1 to 4 depending on the classification of the occupation within the four groups considered.

**Table 2**: The technological classification of occupational terrains.

| | | Automation risk | |
|---|---|---|---|
| | | Low | High |
| Effect of AI advances | High | Rising stars | Machine terrain |
| | Low | Human terrain | Collapsing |

Our *control variables* include information about demographics, employment and the macroeconomic environment. Thus, we control for gender, age, cohabiting status, physical health -measured in a 1-5 scale from *Excellent* (1) to *Poor* (5)-, financial situation

[8] The thresholds for classifying occupations are 70% for the automation probability (this variable takes values from 0.39% to 99% in the sample) and 3 for the AI transformative effect (this variable takes values from 1.509986 to 6.5372 in the sample).

-measured as the ability to make ends meet in a 1-4 scale from *With great difficulty* (1) to *Easily* (4)-, and having higher education. Regarding employment variables, we consider the job status, that includes three categories (employees –private sector–, civil servants – public sector–, self-employed workers), the sector of activity (primary sector, manufacturing and construction, and services) and a variable indicating if the individual is working full time or not. In order to control for macroeconomic environment, we use the real GDP growth, the harmonized unemployment rate and the expenditure in old-aged pensions in PPS per inhabitant.[9] We include a variable collecting the effect of the social security system generosity of the country, as it has a strong effect incentivizing the early retirement decision.[10] Last, we use country and wave dummies.

## 5. Results

This section shows the main results of this study, divided in three parts. First, we depict the descriptive statistics and we show the mapping of occupations for the early retirement transitions in our sample. Second, we analyze the implications of automation probability for the probability of early retirement and we investigate the relation of automation risk with education and job status in the framework of the early retirement transition. Finally, we use the technological classification of occupational terrains in order to explore the implications for a worker of belonging to one particular group of these four (human terrain, rising stars, collapsing occupations and machine terrain). Again, we investigate the relation of this occupational terrains with education and job status regarding the early retirement decisions.

### 5.1. Descriptive statistics and the mapping of early retirement transitions in occupational terrains

In this subsection we comment the descriptive statistics shown in Table A1 and then we offer a vision of the early retirement transitions by occupation in their corresponding

[9] An equivalent measure would by the Expenditure in social protection -old age function- in PPS per inhabitant, also from Eurostat, as both variables are highly correlated and show very similar results.

[10] For OCDE countries it has been documented by Blöndal and Scarpetta (1997). If we want to look for specific example analyzing European countries we can find, for example, Blundell *et al.* (2002) for the case of UK and Börsch-Supan and Jürges (2009) for the case of Germany.

occupational terrains according to the technological classification provided by Fossen and Sorgner (2019).

Table A1 presents the descriptive statistics of our sample. This descriptive statistics are profiled in the first instance for the whole sample, then only for the observations regarding the transitions to early retirement and finally for the rest of the observations.

As we can observe, there are some conspicuous differences in the value of some variables for observations regarding the switch to early retirement and the rest of observations. First, the mean automation probability is a 4% higher when the switch to early retirement is produced, while its standard deviation accounts for 1.5% less. We can also find these differences in the occupational terrains, as, in the switch to early retirement, there are less occupations in the human terrain and the rising stars, and more in the collapsing occupations and the machine terrain. Logically, the proportion of occupations at high automation risk is higher among the switches to early retirement.

About job status, we can find a lower percentage of employees and self-employed while a larger percentage of employees in the transitions to early retirement. As logical, the percentage of workers with higher education is lower among early retirees. Furthermore, we can see that the percentage of occupations in the services sector is lower in early retirement transitions and, as indicated by literature, GDP growth is lower for this observations.

Now that we have resumed the descriptive statistics, we offer a vision of all early retirement transitions in our sample relying on the technological classification in occupational terrains showed in Table 2.

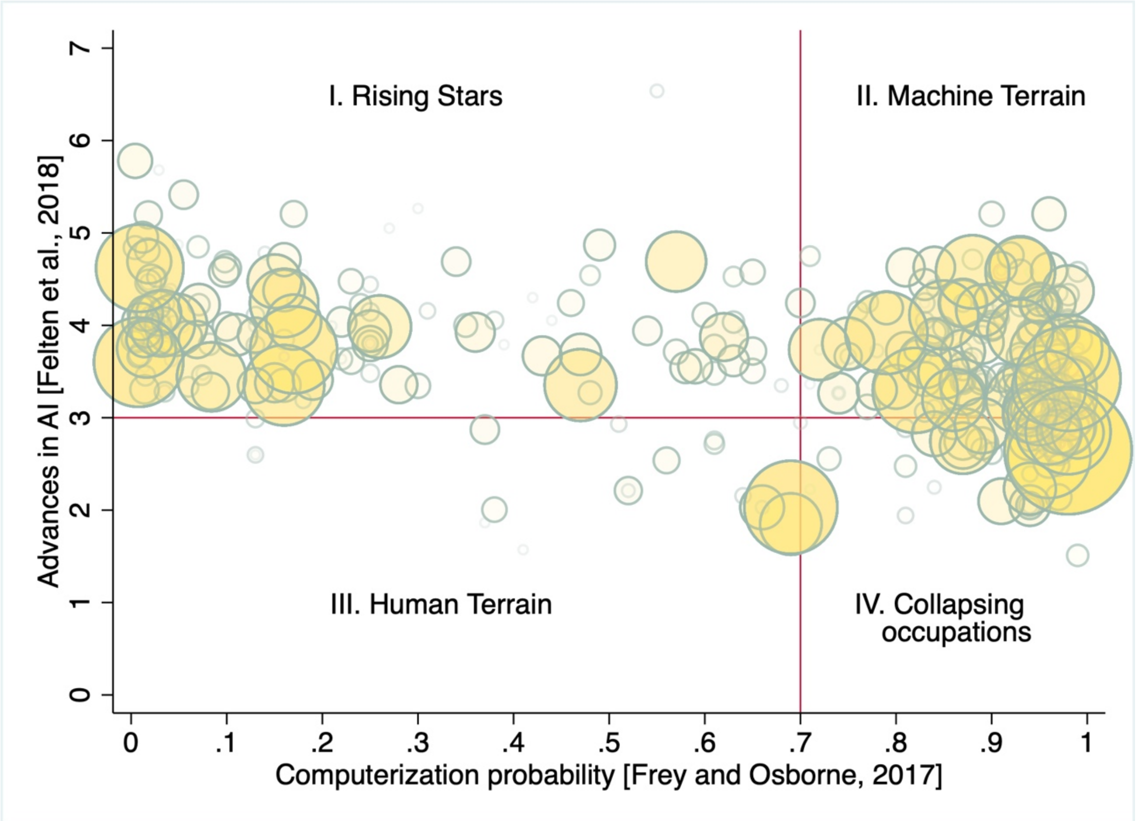


**Figure 1:** Early retirement transitions and the occupational terrains. Compiled by the authors from the SHARE data and considering the technological classification of occupational terrains provided by Fossen and Sorgner (2019).

In Figure 1 we can find a graph collecting 6,408 early retirement transitions from 389 different occupations. Every bubble matches a concrete occupation, being its center at the point determined by its computerization probability in the x-axis and its AI transformative effect measure in the y-axis. The size of each bubble depends on the number of early retirement transitions that took place in the period 2004-2017 from that precise occupation. The two perpendicular red lines delimit the four occupational fields considered in this research[11]. As we can observe, a few early retirement transitions were produced in the square corresponding the human terrain occupations (in fact, only 4% of early retirement transitions were produced in this area. Then, the rest 96% of early retirement transitions were produced in the area surrounding that of the human terrain, the area more affected by technological advances.

[11] As presented in Table 2.

**Table 3**. Early retirement transitions and the occupational terrains

| Occupational terrains | Early retirement transitions | | | | | |
|---|---|---|---|---|---|---|
| | Education | | Job Status | | | Total |
| | No higher | Higher | Employee | Civil servant | Self-employed | |
| Human terrain | 249 | 24 | 171 | 95 | 7 | 273 (4%) |
| Rising stars | 1101 | 993 | 764 | 1103 | 227 | 2094 (33%) |
| Collapsing | 992 | 171 | 739 | 349 | 75 | 1163 (18%) |
| Machine terrain | 2574 | 304 | 1569 | 1043 | 266 | 2878 (45%) |
| Total | 4916 (77%) | 1492 (23%) | 3243 (51%) | 2590 (40%) | 575 (9%) | 6408 |

In Table 3 we can see the data associated with Figure 1. As we anticipated, early retirement transitions from the human terrain accounts only for the 4% of the total transitions. The remaining 96% comes from the other 3 occupational terrains almost equitably (45% from the machine terrain, 18% from the collapsing occupations and 33% from the rising stars occupations). Likewise, only 9% of the early retirement transitions proceed from self-employed workers while the rest come from employees (51%) and civil servants (40%). Finally, only 23% of the early retirement transitions come from workers with higher education while the remaining 77% come from workers without higher education. In other words, for every 4 early retirees only 1 has higher education.

Table 4 adds a deeper dimension respect to Table 3 by incorporating the number of early retirees that account for higher education for every combination of job status and occupational terrain. Then, as we can observe, from the 1569 early retirees that were employees in the machine terrain, only 113 have higher education.

**Table 4**. Early retirement transitions and education level by occupational terrains and job status

<table>
<tr><td rowspan="3">Occupational terrains</td><td colspan="8">Early retirement transitions</td></tr>
<tr><td colspan="2">Employee</td><td colspan="2">Civil servant</td><td colspan="2">Self-employed</td><td colspan="2">Total</td></tr>
<tr><td>NH</td><td>Higher</td><td>NH</td><td>Higher</td><td>NH</td><td>Higher</td><td>NH</td><td>Higher</td></tr>
<tr><td rowspan="2">Human terrain</td><td colspan="2">171</td><td colspan="2">95</td><td colspan="2">7</td><td colspan="2">273 (4%)</td></tr>
<tr><td>161</td><td>10</td><td>84</td><td>11</td><td>4</td><td>3</td><td>249</td><td>24</td></tr>
<tr><td rowspan="2">Rising stars</td><td colspan="2">764</td><td colspan="2">1103</td><td colspan="2">227</td><td colspan="2">2094 (33%)</td></tr>
<tr><td>442</td><td>322</td><td>504</td><td>599</td><td>155</td><td>72</td><td>1101</td><td>993</td></tr>
<tr><td rowspan="2">Collapsing</td><td colspan="2">739</td><td colspan="2">349</td><td colspan="2">75</td><td colspan="2">1163 (18%)</td></tr>
<tr><td>622</td><td>117</td><td>310</td><td>39</td><td>60</td><td>15</td><td>992</td><td>171</td></tr>
<tr><td rowspan="2">Machine terrain</td><td colspan="2">1569</td><td colspan="2">1043</td><td colspan="2">266</td><td colspan="2">2878 (45%)</td></tr>
<tr><td>1415</td><td>154</td><td>933</td><td>110</td><td>226</td><td>40</td><td>2574</td><td>304</td></tr>
<tr><td rowspan="2">Total</td><td colspan="2">3243 (51%)</td><td colspan="2">2590 (40%)</td><td colspan="2">575 (9%)</td><td colspan="2">6408</td></tr>
<tr><td>2640</td><td>603</td><td>1831</td><td>759</td><td>445</td><td>130</td><td>4916</td><td>1492</td></tr>
</table>

Table 5 also complements Figure 1 by presenting the thirty occupations with higher number of early retirement transitions in order to develop a brief qualitative analysis. There we can find the ISCO-08 title of the occupation, the ISCO-08 code, the number of transitions to early retirement from that occupation, its associated computerization probability and measure for the advances in AI and the occupational terrain to which the occupation belongs to.

Within this 30 occupations with higher early retirement transitions, we find 7 occupations in the collapsing terrain, 12 in the machine terrain, 10 rising star occupations and 1 single occupation from the human terrain. Furthermore, we must bear in mind that this occupation from the human terrain accounts for a 0.69 computerization probability so it is just 0.01 of computerization probability away from being a collapsing occupation.

We find that 13 of these occupations (almost half) have an associated computerization probability higher than 0.9. By contrast, we also find 4 occupations with less than 0.1 of computerization probability. In sum, the 30 occupations from Table 10 account for 2,569 early retirement transitions, which means that the 8% of the 373 occupations account for the 40% of the total 6,408 early retirement transitions.

**Table 5.** Early retirement transitions and occupation titles

| | ISCO-08 Title | ISCO-08 | Early retirement | Comp. Prob. | Advances in AI | Occupational terrain |
|---|---|---|---|---|---|---|
| 1 | General office clerks | 4110 | 235 | .98 | 2.515487 | Collapsing occupation |
| 2 | Shop sales assistants | 5223 | 159 | .98 | 3.4247646 | Machine terrain |
| 3 | Cleaners and helpers in offices, hotels and other establishments | 9112 | 125 | .69 | 1.864328 | Human terrain |
| 4 | Secondary education teachers | 2330 | 115 | .0078 | 3.6010003 | Rising star |
| 5 | Nursing professionals | 2221 | 110 | .009 | 4.5649738 | Rising star |
| 6 | Primary school teachers | 2341 | 109 | .17 | 3.7339506 | Rising star |
| 7 | Accounting associate professionals | 3313 | 104 | .98 | 2.8479018 | Collapsing occupation |
| 8 | Bricklayers and related workers | 7112 | 104 | .82 | 3.295743 | Machine terrain |
| 9 | Secretaries (general) | 4120 | 99 | .96 | 2.5797276 | Collapsing occupation |
| 10 | Heavy truck and lorry drivers | 8332 | 97 | .79 | 3.663444 | Machine terrain |
| 11 | Shopkeepers | 5221 | 93 | .16 | 3.3521471 | Rising star |
| 12 | Cooks | 5120 | 78 | .96 | 2.8938298 | Collapsing occupation |
| 13 | Agricultural and industrial machinery mechanics and repairers | 7233 | 77 | .88 | 4.5108662 | Machine terrain |
| 14 | Health care assistants | 5321 | 74 | .47 | 3.3536105 | Rising star |
| 15 | Motor vehicle mechanics and repairers | 7231 | 69 | .93 | 3.5198073 | Machine terrain |
| 16 | Freight handlers | 9333 | 68 | .85 | 2.7752922 | Collapsing occupation |
| 17 | Child care workers | 5311 | 68 | .084 | 3.2662568 | Rising star |
| 18 | Manufacturing labourers not elsewhere classified | 9329 | 67 | .93 | 3.1929021 | Machine terrain |
| 19 | Managing directors and chief executives | 1120 | 67 | .16 | 4.2420411 | Rising star |
| 20 | Car, taxi and van drivers | 8322 | 66 | .98 | 3.663444 | Machine terrain |
| 22 | University and higher education teachers | 2310 | 63 | .032 | 3.7161329 | Rising star |
| 21 | Toolmakers and related workers | 7222 | 62 | .93 | 3.4915924 | Machine terrain |
| 23 | Accounting and bookkeeping clerks | 4311 | 61 | .96 | 2.327374 | Collapsing occupation |
| 24 | Subsistence crop farmers | 6310 | 61 | .87 | 2.7472272 | Collapsing occupation |
| 25 | Accountants | 2411 | 59 | .99 | 3.6984756 | Machine terrain |
| 26 | Mail carriers and sorting clerks | 4412 | 58 | .95 | 3.0472412 | Machine terrain |
| 27 | Vocational education teachers | 2320 | 56 | .26 | 3.9857595 | Rising star |
| 28 | Electrical mechanics and fitters | 7412 | 55 | .93 | 3.9260128 | Machine terrain |
| 29 | Administrative and executive secretaries | 3343 | 55 | .86 | 3.1940594 | Machine terrain |
| 30 | Agricultural and forestry production managers | 1311 | 55 | .047 | 4.0065403 | Rising star |

### 5.2. Early retirement and automation risk

Here we demonstrate the significance of the automation probability in the early retirement decisions and then show differentiated effects of automation risk with respect to higher education and job status.

Table 6 collects six estimations of logit models. The first four estimations consider the automation probability as the main explicative variable for the early retirement transition. The first estimation controls for gender, age, cohabiting status, health and financial situation and includes country and wave dummies. The second estimation also controls for higher education. The third estimation adds the job characteristics controls: job status, full time, and sector. The last estimation considering the automation probability in percentage also controls for macroeconomic variables: GDP growth, harmonized unemployment rate and old age pensions in pps per inhabitant. In all of these four estimations, the main explicative variable, automation probability in percentage, is significant at a 1% level. The marginal effect of the variable is only reduced when the control for higher education is added, remaining constant in the other 3 estimations with increasing controls.

The result of the first estimation is telling us that an increase of 1% in the automation probability augments, in average, the probability of early retirement by 0.23%. In the estimations II-IV an increase of 1% in the automation probability would rise the probability of early retirement by 0.11%. It may seem like a small effect, but this means, in the case of the first estimate, increasing the probability of early retirement by 23% when traversing the spectrum of the variable. We must also bear in mind that the effect can largely vary between different individuals. In fact, as we observe in Figures 2 and 3 and Tables 7 and 8, we find differentiated effects for higher education and job status.

In estimations V and VI we consider all controls and furthermore, interactions of automation risk with education and job status, that would redound in the aforementioned differentiated effects. Specifically, model V collects the interaction between automation risk and education, and from this model we plot graphs in Figure 2 and present the associated Table 7. For its part, model VI reflects the interaction between automation risk and job status and this model is used to obtain Figure 3 and the related Table 8.

**Table 6**. Determinants of early retirement transitions with special focus on automation probability (Frey and Osborne, 2017) – Logit estimations

| Model | I | | II | | III | | IV | | V | | VI | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Predicted probability (y) | 0.0529 | | 0.0529 | | 0.0529 | | 0.0529 | | 0.0529 | | 0.0529 | |
| Independent variables (x) | dy/dx | z-stat | dy/dx | z-stat | dy/dx | z-stat | dy/dx | z-stat | dy/dx | z-stat | dy/dx | z-stat |
| *Main regressors* | | | | | | | | | | | | |
| Automation probability (%) | 1.24E-04 | 7.42 *** | 5.95E-05 | 3.32 *** | 5.69E-05 | 3.12 *** | 5.74E-05 | 3.15 *** | | | | |
| High automation risk[a] | | | | | | | | | 0.0046 | 3.50 *** | 0.0047 | 3.52 *** |
| *Controls* | | | | | | | | | | | | |
| Female[a] | 0.0205 | 15.99 *** | 0.0204 | 15.95 *** | 0.0242 | 17.36 *** | 0.0243 | 17.45 *** | 0.0245 | 17.56 *** | 0.0245 | 17.54 *** |
| Age | 0.0184 | 76.96 *** | 0.0185 | 77.16 *** | 0.0186 | 77.6 *** | 0.0187 | 77.64 *** | 0.0187 | 77.64 *** | 0.0187 | 77.65 *** |
| With partner[a] | 0.0052 | 3.53 *** | 0.0048 | 3.28 *** | 0.0053 | 3.65 *** | 0.0052 | 3.57 *** | 0.0053 | 3.59 *** | 0.0052 | 3.58 *** |
| Health (ref. Excellent) | | | | | | | | | | | | |
| Very good | 0.0046 | 2.02 ** | 0.0045 | 1.94 * | 0.0041 | 1.77 * | 0.0040 | 1.75 * | 0.0040 | 1.71 * | 0.0039 | 1.70 * |
| Good | 0.0109 | 5.07 *** | 0.0102 | 4.68 *** | 0.0097 | 4.48 *** | 0.0098 | 4.48 *** | 0.0097 | 4.45 *** | 0.0098 | 4.48 *** |
| Fair | 0.0180 | 7.55 *** | 0.0167 | 6.93 *** | 0.0167 | 6.92 *** | 0.0166 | 6.87 *** | 0.0166 | 6.87 *** | 0.0166 | 6.87 *** |
| Poor | 0.0244 | 6.98 *** | 0.0230 | 6.59 *** | 0.0232 | 6.61 *** | 0.0231 | 6.6 *** | 0.0231 | 6.58 *** | 0.0231 | 6.59 *** |
| Ability to make ends meet (ref. With great difficulty) | | | | | | | | | | | | |
| With some difficulty | 0.0036 | 1.51 | 0.0039 | 1.63 | 0.0037 | 1.56 | 0.0040 | 1.69 * | 0.004 | 1.70 * | 0.004 | 1.70 * |
| Fairly easily | 0.0017 | 0.7 | 0.0028 | 1.17 | 0.0026 | 1.07 | 0.0028 | 1.17 | 0.0028 | 1.16 | 0.0028 | 1.17 |
| Easily | -0.0003 | -0.14 | 0.0020 | 0.82 | 0.0018 | 0.74 | 0.0019 | 0.78 | 0.0018 | 0.74 | 0.0019 | 0.75 |
| *Education* | | | | | | | | | | | | |
| Tertiary education[a] | | | -0.0146 | -10.33 *** | -0.0153 | -10.77 *** | -0.0153 | -10.83 *** | -0.016 | -11.24 *** | -0.0155 | -11.1 *** |
| *Job characteristics* | | | | | | | | | | | | |
| Job status (ref. Employee) | | | | | | | | | | | | |
| Civil servant | | | | | 0.0095 | 6.21 *** | 0.0093 | 6.09 *** | 0.0092 | 6.01 *** | 0.0094 | 6.18 *** |
| Self-employed | | | | | -0.0173 | -10.46 *** | -0.0173 | -10.47 *** | -0.0173 | -10.51 *** | -0.0174 | -10.58 *** |
| Full time[a] | | | | | 0.0143 | 8.17 *** | 0.0143 | 8.16 *** | 0.0142 | 8.07 *** | 0.0141 | 8.04 *** |
| Sector (ref. Primary) | | | | | | | | | | | | |
| Manufacturing and Construction | | | | | 0.0017 | 0.67 | 0.0016 | 0.64 | 0.0018 | 0.72 | 0.0013 | 0.52 |
| Services | | | | | -0.0081 | -3.4 *** | -0.0082 | -3.46 *** | -0.0078 | -3.26 *** | -0.0082 | -3.42 *** |
| *Macroeconomic variables* | | | | | | | | | | | | |
| GDP growth | | | | | | | -0.0003 | -1.1 | -0.0003 | -1.12 | -0.0003 | -1.11 |
| Harmonised unemployment rate | | | | | | | 0.0013 | 5.15 *** | 0.0013 | 5.14 *** | 0.0012 | 5.10 *** |
| Old age pensions pps per capita | | | | | | | 9.7E-06 | 1.92 * | 9.6E-06 | 1.89 * | 9.9E-06 | 1.95 * |
| Country dummies (ref. Spain) | Yes | | Yes | | Yes | | Yes | | Yes | | Yes | |
| Wave dummies (ref. 2004) | Yes | | Yes | | Yes | | Yes | | Yes | | Yes | |
| Log likelihood | -19,094.3 | | -19,045.2 | | -18,910.6 | | -18,892.9 | | -18,890.9 | | -18,888.9 | |
| #obs | 121,026 | | 121,026 | | 121,026 | | 121,026 | | 121,026 | | 121,026 | |

Notes: : * 0,1 >$p \geq$ 0,05; ** 0,05 >$p \geq$ 0,01; *** $p$< 0,01. [a] Dummy variable. Model V includes interaction terms between high automation risk and tertiary education variables. Model VI includes interaction terms between automation risk and job status variables.

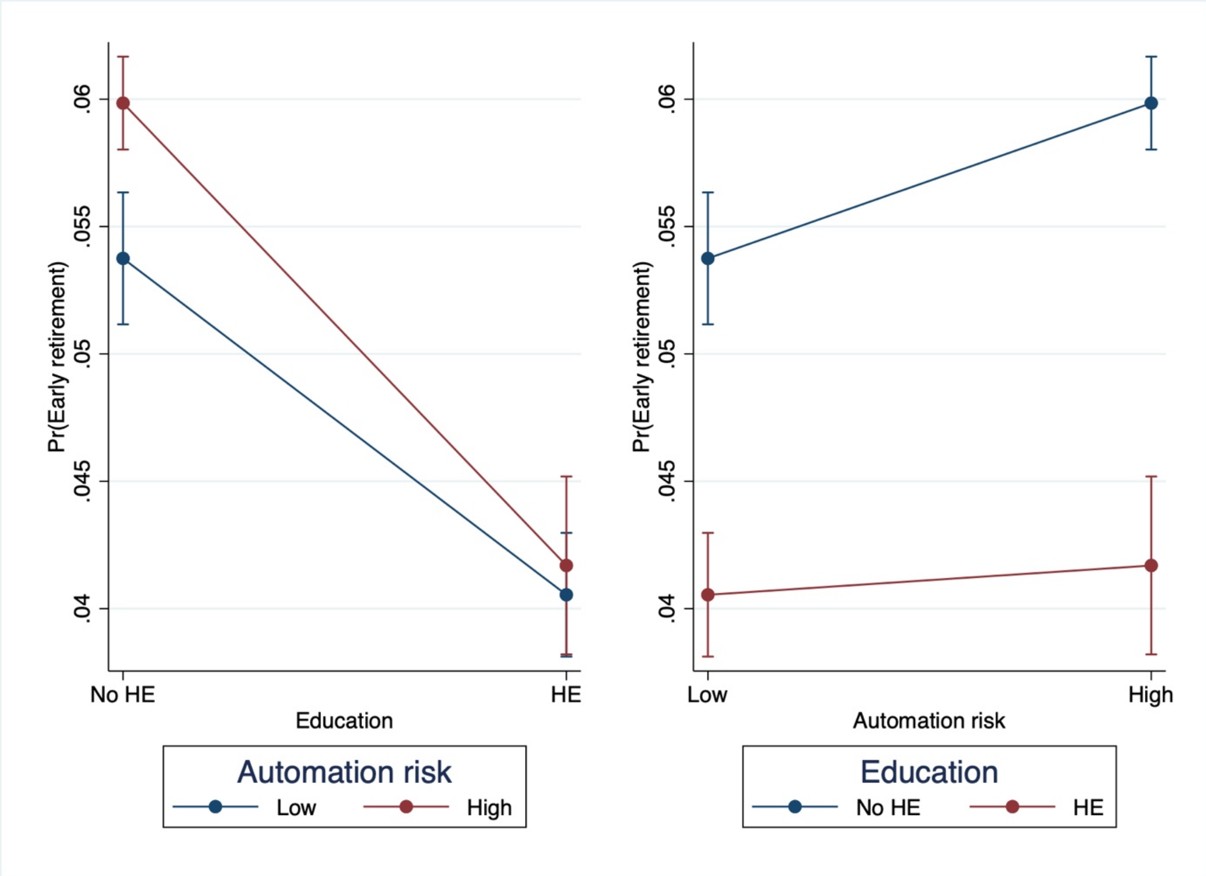


**Figure 2**: Early retirement probability, education and automation risk.
*Note*: Predicted probabilities and marginal effects are from model V in Table 3.

**Table 7**. Predicted probabilities of early retirement and marginal effects by educational attainment and automation risk.

| | Predicted probability of early retirement | | Marginal effect of automation risk | | | | Marginal effect of higher education | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Education** | No HE | HE | No HE | | HE | | No HE | | HE | |
| | | | dy/dx | z-stat | dy/dx | z-stat | dy/dx | z-stat | dy/dx | z-stat |
| **Automation risk** | | | | | | | | | | |
| Low | 0.0538 | 0.0405 | *Ref.* | | *Ref.* | | *Ref.* | | -0.0132 | -7.30 *** |
| High | 0.0598 | 0.0417 | 0.0061 | 3.75 *** | 0.0011 | 0.54 | *Ref.* | | -0.0182 | -8.94 *** |

Figure 2 and Table 7 are closely related. In fact, the two graphs in Figure 2 are giving us the same information from two different perspectives just as Table 7 complements these two views of that same information. As we observe, the difference between the right-graph and the left-graph in Figure 2 is that the lines of the one are the x-axis of the other.

We can interpret the left-side graph as the change in the probability of early retirement when an individual obtains higher education depending on the automation risk of his job. Then, the right-side graph is telling us how the probability of early retirement evolves when and individual transit from an occupation with low automation risk to an occupation with high automation risk depending on having higher education or not.

In the left-side graph we can appreciate how the probability of early retirement diminishes when the individual has higher education, independently of the automation risk. The main information that we obtain from this graph is that higher education acts as a shield against automation. In fact, for a higher educated individual, the affectation of automation risk is not significant. As we can see in the graph, the confidence intervals for the low and high automation risks are well differentiated in the case in which the individual has no higher education, while these intervals intermingle in the case in which the individual has higher education. Therefore, the probability of early retirement always drops when an individual obtains higher education and this drop is larger when the occupation has high automation risk.

In the right-side graph, we can observe the different slopes respect to the probability of early retirement when switching from low to high automation risk for individuals with higher and no higher education. This slope is evidently more pronounce for individuals with no higher education while the slope for individuals with higher education is almost flat. Indeed, if we focus on the confidence intervals, they are perfectly differentiated for individuals with no higher education as the probability of early retirement is significantly larger when the individual carries out a job with high automation risk. For the case of higher educated workers, the probability of early retirement does not increase significantly when switching from low automation risk occupation to a high automation risk occupation, as the confidence intervals at the right and the left of the x-axis are not in difference positions from the perspective of the y-axis.

We can find an explanation for this phenomenon by arguing that workers with different levels of training can generate different levels of added value even if they perform the same tasks in the same occupation. This would be another level of heterogeneity to that proposed by Arntz et al. (2016, 2017). If these authors argue that the tasks of the same occupation in different sectors or companies can vary widely, we can go further to affirm that the same tasks from the same occupation, even in the same firm, carried out by workers with different training levels can derive in very different outcomes. In fact, at the end of the day is a matter of profits maximization. If a firm accounts for the technology to automatized an occupation and the worker who performs this occupation is not very productive and does not add value to the firm further the frontiers of his occupation, this worker is very likely to go inactive (if he is a middle-age worker, his probability of early retirement will be high). However, if a firm accounts for the technology to automatized an occupation but the worker who performs this occupation has higher education, is very productive and an important value added to the firm, this worker is very likely to remain in his job spot avoiding the automation process.

To sum up, we find that workers with no higher education and high automation probability are more likely to take the early retirement decision. On the other hand, individuals with higher education are less likely to retire early independently of the automation risk. Then, we obtain that, while getting higher education drops the early retirement probability for both workers at low and high automation risk, the transit from a low risk to a high automation risk occupation only increases the probability of early retirement significantly for individuals with no higher education. As we aforementioned, the main message collected by Figure 1 and Table 4 is that, for middle-age workers, obtaining higher education is to get a shield against early retirement caused by automation.

Figure 3 and Table 8 collects the relation between job status and automation risk regarding the probability of early retirement. Again, the two graphs in the Figure and the Table are providing the same information from different perspectives, allowing us to obtain a full vision of the interconnection.

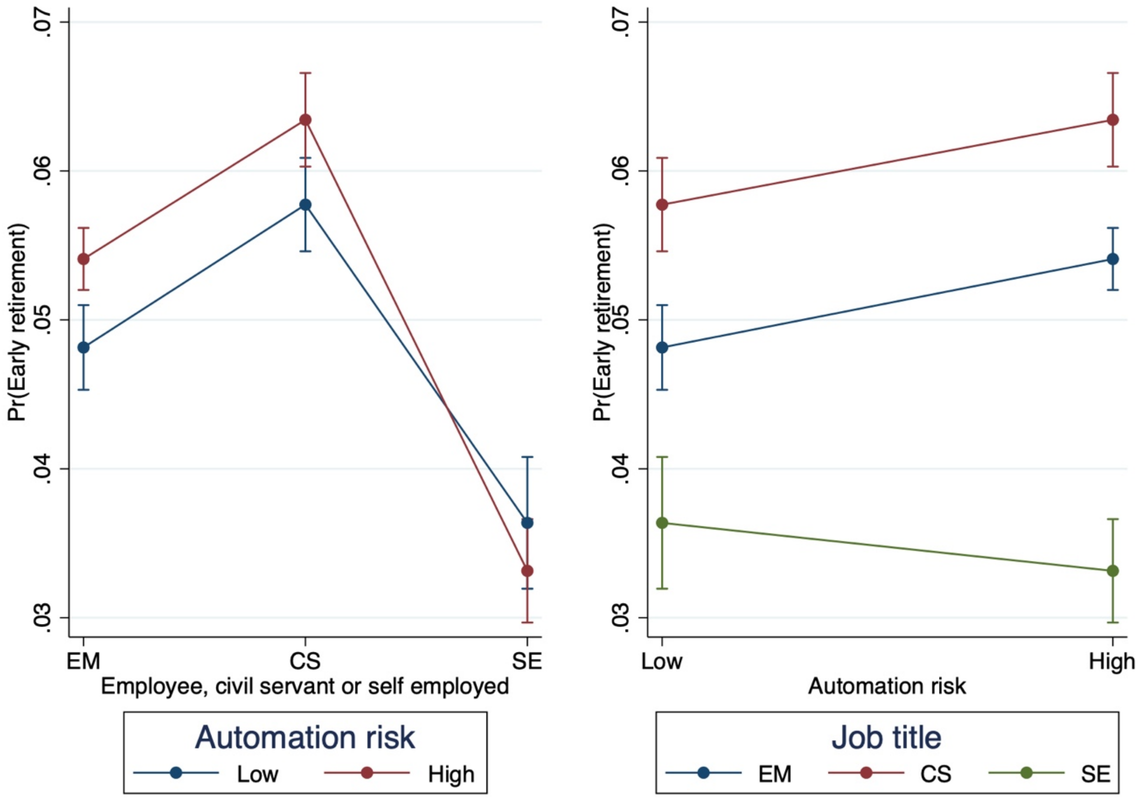


**Figure 3**: Early retirement probability, job status and automation risk.
*Note*: Predicted probabilities and marginal effects are from model VI in Table 3.

**Table 8**. Predicted probabilities of early retirement and marginal effects by job status and automation risk.

| | Predicted probability of early retirement | | | Marginal effect of automation risk | | | | | | Marginal effect of job status | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Job status** | EM | CS | SE | EM | | CS | | SE | | EM | CS | | SE | |
| | | | | dy/dx | z-stat | dy/dx | z-stat | dy/dx | z-stat | | dy/dx | z-stat | dy/dx | z-stat |
| **Automation risk** | | | | | | | | | | | | | | |
| Low | 0.0481 | 0.0577 | 0.0364 | *Ref.* | | *Ref.* | | *Ref.* | | *Ref.* | 0.0096 | 4.45 *** | -0.0118 | -4.42*** |
| High | 0.0541 | 0.0634 | 0.0331 | 0.0059 | 3.32*** | 0.0057 | 2.55* | -0.0032 | -1.13 | *Ref.* | 0.0093 | 4.77 *** | -0.0209 | -10.22*** |

In the graph on the left side of Figure 3, we see three different categories of job status: employee, civil servant and self-employed. Within the graph, the red lines and spots collect the connection between workers with high automation risk in the different job status respect to the probability of early retirement. The blue lines and spots, reflects this vision for workers at low automation. As expected, civil servants are the individuals with higher probability of early retirement, followed by employees and far behind by self-employed. If we observe the confidence intervals within the graph (together with the center columns of Table 8), we appreciate that high automation risk carries out a high probability of early retirement for employees (at a significance level of 1%) and civil servants (at a significance level of 10%). Nevertheless, the levels of automation risk intersect in the case of the self-employed workers and the confidence intervals intermingle, showing the imperturbability of their early retirement probability regarding automation process. Interestingly, if we look at the confidence intervals for employees with high automation risk and civil servants with low automation risk, we can appreciate that they cover common areas from the point of view of the y-axis. This would mean that, although civil servants possess larger probability of early retirement than employees, this probability is similar for employees with high automation risk and civil servants with low automation risk.

In the right-side graph of Figure 3 we can observe how the probability of early retirement change for workers going from a low to a high automation risk depending on their job status. The red lines and dots collect the effect for civil servants, the blue lines and dots present the switch for employees and the green lines and dots reflect the case of self-employed workers. At first sight, the effect is similar for employees and civil servants while varying largely for self-employed workers (being opposite, in fact). On the one hand, for the cases of civil servants and employees, we find positive slopes of same dimensions at different levels. On the other hand, for the case of self-employed workers, we find a negative slope reflecting that the probability of early retirement decreases when the automation risk increases, but not significantly. As we can observe in the right-side of Table 8, the differences in the probability of early retirement between the three categories of job status are significant at a 1% level in both scenarios of low and high automation risk. Then, while the probability of early retirement for employees and civil servants is increasing respect to automation probability, the probability of early retirement for self-employed individuals seems to be unaltered by automation probability.

We can also obtain this information by focusing on the large separation between all confidence intervals in the left-side graph of Figure 3. Further, we should remark that, by observing at the confidence intervals in this graph from the perspective of the y-axis we remark the information provided before: the increase of automation risk augments the probability of early retirement for employees at a significance of 1% and for civil servants at 10%, while remaining unaffected the self-employed workers. This is important because, although we observe a negative slope for the case of self-employed workers, the large confidence intervals indicate that this descend in the probability of early retirement is not significant. Nevertheless, the gap in the early retirement probability between employees (in the private or public sector) and the self-employed is wider in a context of high automation risk rather than in one of low automation risk. This can be ascertain by focusing on the distance between the lower limit of confidence interval for employees and the upper limit of confidence interval for self-employed in both the low automation risk situation (left-side of x-axis) and the high automation risk situation (right-side of x-axis).

In summary, the main message from Figure 3 and Table 8 is that self-employment is a good refuge from automation for middle-age workers seeking to achieve their statutory retirement ages in a high automation risk context.

### 5.3.Early retirement and the occupational terrains

Now that we have observed how the computerization probability affects the early retirement decisions, we consider the technological classification of occupations provided by Fossen and Sorgner (2019) in order to investigate how the belonging to a certain group -human terrain, rising stars, collapsing occupations or machine terrain- can affect the probability of early retirement of an individual.

Following the previous procedure to measure the impact of automation probability, we consider for models with the same control levels in crescendo and the occupational terrains as the main explicative variable. As we can appreciate in Table 9, the probability of early retirement increase significantly for workers in rising star occupations, collapsing occupations and occupations in the machine terrain as compared with workers in occupations from the human terrain (the reference group). This is observe in models VIII-XII while in model VII the increase in the probability of early retirement for workers in a rising star occupation is not significantly different with respect to that of the workers in the human terrain occupations. The significance level of early retirement probability differentiation remain at the maximum in all estimations for workers in the collapsing occupations and the machine terrain occupations respect to workers in the human terrain occupation. In contrast, this significance level switch among estimations for workers in rising stars occupations respect to human terrain workers.

Models XI and XII collects interactions of the occupational terrains with respect to education and job status respectively. From model XI, we obtain Figure 4 and Table 10. From model XII, we have Figure 5 and Table 11. Within these Figures and Tables we explored the differentiated effects for distinct education levels and job status regarding this 4-groups occupational classification and the probability of early retirement.

Figure 4 and Table 10 show the interaction between the 4 groups of occupations and the two levels of education considered. In the graph on the left of Figure 4, we see how the probability of early retirement varies for individuals in the different occupational groups depending on the level of education. As we may observe, both in the graph and in the first columns of Table 10, the lowest predicted probabilities of early retirement are given for individuals with higher education in the human terrain and the machine terrain. This seems like a curious result indicating that, while it is logical that individuals in the human terrain with higher education are the less likely to go for early retirement, we must also bear in mind that new technology occupying the machine terrain are developed, established and controlled by higher educated workers with a crucial role in the technological change (engineers, computer scientists, etc).

**Table 9**. Determinants of early retirement transitions with special focus on the occupational terrains (Fossen and Sorgner, 2019) – Logit estimations

| Model | VII | | VIII | | IX | | X | | XI | | XII | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Predicted probability (y) | 0.0529 | | 0.0529 | | 0.0529 | | 0.0529 | | 0.0529 | | 0.0529 | |
| Independent variables (x) | dy/dx | z-stat | dy/dx | z-stat | dy/dx | z-stat | dy/dx | z-stat | dy/dx | z-stat | dy/dx | z-stat |
| *Main regressors* | | | | | | | | | | | | |
| Occupational terrains (*ref.* Human terrain) | | | | | | | | | | | | |
| Rising stars | 0.0026 | 0.94 | 0.0076 | 2.77 *** | 0.0058 | 2.04 ** | 0.0055 | 1.95 * | 0.0056 | 1.86 * | 0.0052 | 1.71 * |
| Collapsing | 0.0123 | 4.18 *** | 0.0124 | 4.34 *** | 0.0110 | 3.74 *** | 0.0108 | 3.65 *** | 0.0118 | 3.68 *** | 0.0105 | 3.29 *** |
| Machine terrain | 0.0110 | 3.97 *** | 0.0109 | 4.09 *** | 0.0088 | 3.16 *** | 0.0086 | 3.10 *** | 0.0085 | 2.82 *** | 0.0085 | 2.81 *** |
| *Controls* | | | | | | | | | | | | |
| Female[a] | 0.0208 | 15.59 *** | 0.0208 | 15.59 *** | 0.0241 | 16.84 *** | 0.0243 | 16.93 *** | 0.0243 | 16.97 *** | 0.0242 | 16.84 *** |
| Age | 0.0184 | 76.95 *** | 0.0185 | 77.18 *** | 0.0186 | 77.62 *** | 0.0187 | 77.66 *** | 0.0187 | 77.66 *** | 0.0187 | 77.65 *** |
| With partner[a] | 0.0052 | 3.54 *** | 0.0048 | 3.27 *** | 0.0053 | 3.65 *** | 0.0052 | 3.56 *** | 0.0052 | 3.57 *** | 0.0052 | 3.56 *** |
| Health (ref. Excellent) | | | | | | | | | | | | |
| Very good | 0.0045 | 1.99 ** | 0.0044 | 1.93 * | 0.0040 | 1.75 * | 0.0040 | 1.74 * | 0.0040 | 1.74 * | 0.0039 | 1.71 * |
| Good | 0.0110 | 5.12 *** | 0.0102 | 4.73 *** | 0.0098 | 4.52 *** | 0.0098 | 4.52 *** | 0.0098 | 4.53 *** | 0.0098 | 4.52 *** |
| Fair | 0.0183 | 7.66 *** | 0.0169 | 7.04 *** | 0.0169 | 7.01 *** | 0.0168 | 6.96 *** | 0.0168 | 6.95 *** | 0.0168 | 6.95 *** |
| Poor | 0.0245 | 7.02 *** | 0.0232 | 6.65 *** | 0.0233 | 6.65 *** | 0.0233 | 6.64 *** | 0.0233 | 6.64 *** | 0.0232 | 6.62 *** |
| Ability to make ends meet (ref. With great difficulty) | | | | | | | | | | | | |
| With some difficulty | 0.0035 | 1.43 | 0.0037 | 1.58 | 0.0036 | 1.50 | 0.0039 | 1.64 | 0.0039 | 1.64 | 0.0039 | 1.65 * |
| Fairly easily | 0.0014 | 0.57 | 0.0025 | 1.06 | 0.0023 | 0.97 | 0.0025 | 1.07 | 0.0026 | 1.08 | 0.0025 | 1.06 |
| Easily | -0.0009 | -0.38 | 0.0016 | 0.63 | 0.0014 | 0.56 | 0.0015 | 0.61 | 0.0016 | 0.63 | 0.0015 | 0.6 |
| *Education* | | | | | | | | | | | | |
| Tertiary education[a] | | | -0.0153 | -10.95 *** | -0.0159 | -11.33 *** | -0.0160 | -11.39 *** | -0.0166 | -11.51 *** | -0.0159 | -11.26 *** |
| *Job characteristics* | | | | | | | | | | | | |
| Job status (ref. Employee) | | | | | | | | | | | | |
| Civil servant | | | | | 0.0094 | 6.12 *** | 0.0092 | 6,01 *** | 0.0091 | 5.95 *** | 0.0094 | 6.11 *** |
| Self-employed | | | | | -0.0175 | -10.63 *** | -0.0175 | -10.63 *** | -0.0174 | -10.52 *** | -0.0177 | -10.53 *** |
| Full time[a] | | | | | 0.0139 | 7.85 *** | 0.0139 | 7.85 *** | 0.0139 | 7.86 *** | 0.0139 | 7.82 *** |
| Sector (ref. Primary) | | | | | | | | | | | | |
| Manufacturing and Construction | | | | | 0.0019 | 0.75 | 0.0018 | 0.71 | 0.0019 | 0.74 | 0.0014 | 0.56 |
| Services | | | | | -0.0076 | -3.20 *** | -0.0078 | -3.27 *** | -0.0077 | -3.23 *** | -0.0081 | -3.38 *** |
| *Macroeconomic variables* | | | | | | | | | | | | |
| GDP growth | | | | | | | -0.0003 | -1.12 | -0.0003 | -1.13 | -0.0003 | -1.13 |
| Harmonised unemployment rate | | | | | | | 0.0012 | 5.10 *** | 0.0012 | 5.07 *** | 0.0012 | 5.06 *** |
| Old age pensions pps per capita | | | | | | | 9.7E-06 | 1.9 * | 9.5E-06 | 1.87 * | 9.8E-06 | 1.94 * |
| Country dummies (ref. Spain) | Yes | | Yes | | Yes | | Yes | | Yes | | Yes | |
| Wave dummies (ref. 2004) | Yes | | Yes | | Yes | | Yes | | Yes | | Yes | |
| Log likelihood | -19,094.3 | | -19,039.4 | | -18,906.7 | | -18,889.3 | | -18,886.4 | | -18,885.8 | |
| #obs | 121,026 | | 121,026 | | 121,026 | | 121,026 | | 121,026 | | 121,026 | |

Notes: : * 0,1 >$p \geq$ 0,05; ** 0,05 >$p \geq$ 0,01; *** $p<$ 0,01. [a] Dummy variable. Model XI includes interaction terms between occupational terrains and tertiary education variables. Model XII includes interaction terms between occupational terrains and job status variables.

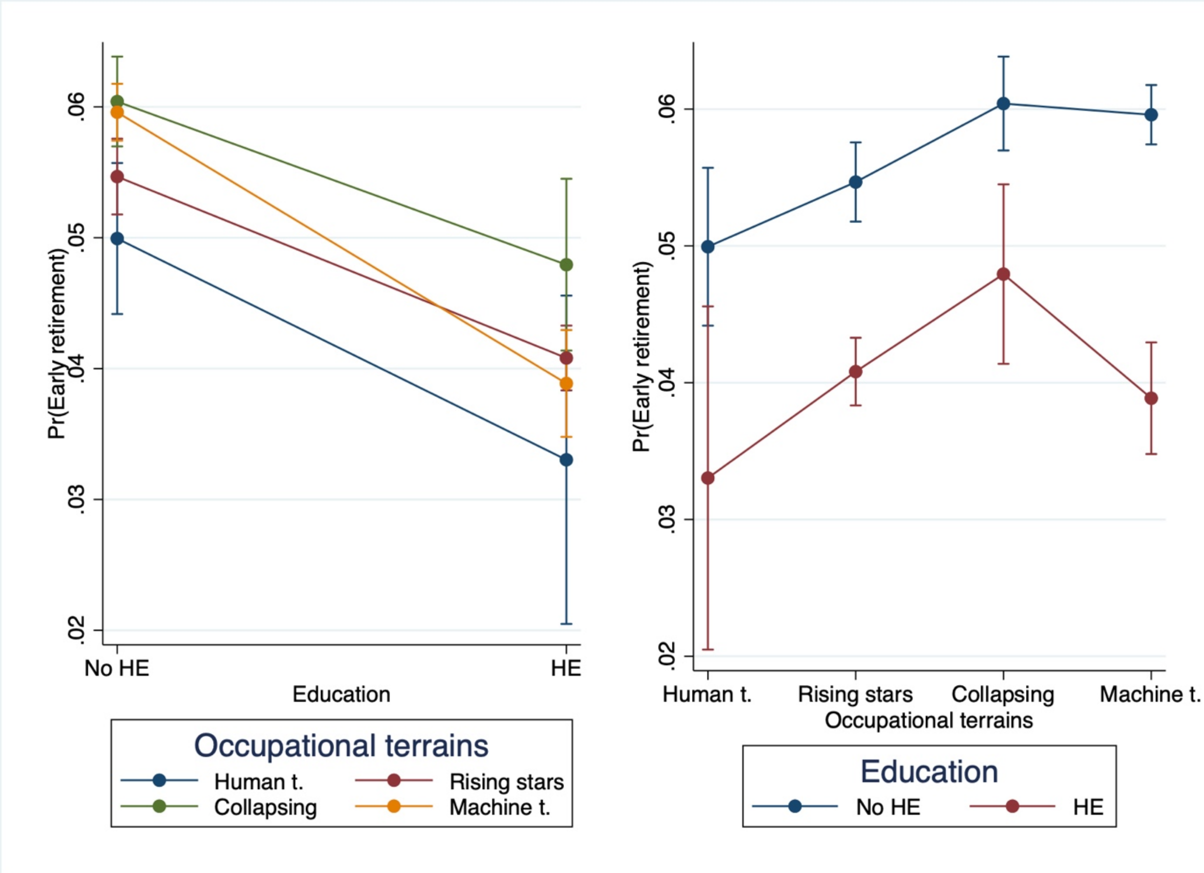


**Figure 4:** Early retirement probability, education and the occupational terrains
*Note*: Predicted probabilities and marginal effects are from model XI in Table 6.

**Table 10**. Predicted probabilities of early retirement and marginal effects by educational attainment and the occupational terrains.

| | Predicted probability of early retirement | | Marginal effect of future occupations | | | | Marginal effect of higher education | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Education** | No HE | HE | No HE | | HE | | No HE | | HE | |
| | | | dy/dx | z-stat | dy/dx | z-stat | dy/dx | z-stat | dy/dx | z-stat |
| **Occupational terrains** | | | | | | | | | | |
| Human terrain | 0.0499 | 0.0330 | *Ref.* | | *Ref.* | | *Ref.* | | -0.0169 | -2.41 ** |
| Rising stars | 0.0547 | 0.0408 | 0.0047 | 1.44 | -0.0078 | 1.19 | *Ref.* | | -0.0139 | -7.17 *** |
| Collapsing | 0.0604 | 0.0479 | 0.0105 | 3.11 *** | 0.0149 | 2.07 ** | *Ref.* | | -0.0125 | -3.31 *** |
| Machine terrain | 0.0596 | 0.0389 | 0.0097 | 3.04 *** | 0.0058 | 0.87 | *Ref.* | | -0.0207 | -8.75 *** |

As we can observe in the center of Table 10 and the confidence intervals of the left-graph in Figure 4, the probability of early retirement is significantly larger for workers with no higher education in a collapsing occupation or in an occupation of the machine terrain taking as a reference workers with no higher education in the human terrain. For the case of workers with higher education, only the workers in a collapsing occupation have larger probabilities of early retirement respect to workers in the human terrain.

Moreover, the right-side graph in Figure 4 tells that the early retirement probability for workers with higher education is always lower that this probability for workers with no higher education in the same occupational group. This information can also be found in the right columns of Table 10, where we can see that having higher education level always reduce the early retirement probability with a significance level of 1% at any occupational group. This descend in the probability of early retirement when change from having no higher education to get higher education is larger when the worker operates in the machine terrain.

If we observe in this graph the red point corresponding to collapsing occupations from the point of view of the y-axis, we see that this point falls within the confidence interval for workers without higher education in the human terrain. This fact indicates us that a worker with higher education in a collapsing occupation could have a similar probability of early retirement than a worker with no higher education in the human terrain.

To sum up, Figure 4 and Table 10 tell us that the safest refuge to hide from early retirement caused by the current technological change is to work in the human terrain having higher education, while the highest probabilities of early retirement are found for workers without higher education in collapsing occupations, the machine terrain, and the rising stars occupations, in that order. It results very logical since, although Fossen and Sorgner (2019) interpret the rising stars occupations as the occupations of the future -logically because of the high productivity due to AI complementarity with human labor-, we must bear in mind that these occupations require a high qualification level so workers with higher education have the full competitive advantage respect to those without higher education.

In addition, for some workers the idea exposed previously that in order to avoid early retirement caused by automation it would be necessary to obtain higher education or become an entrepreneur may sound utopic, and these results are providing a new perspective: maybe it is not fully necessary to get higher education or become self-employed but to look for a job in the human terrain.

In fact, it would be delusional to think that all middle-age workers who have performed the same job (now at high risk of automation) for decades will easily obtain higher education or start a successful business overnight. There is a large heterogeneity of characteristics between individuals in the same risky situation of early exist of the labor market caused by new technologies and that is why the higher number of possible solutions, the richer baseline information we will have to elaborate fruitful policies.

The message here is this: for middle-aged workers who are unwilling to pursue higher education or start their own business, the best way to enlarge their working lives at least until retirement age is to look for a job in the human terrain occupations[12]. Then, the concrete policies designed for these workers should put the focus on relocate them from the machine terrain, collapsing occupations, and rising stars occupations to the human terrain occupations.

We must also consider that, for some workers -like those with no higher education in a rising star occupation - the increase in the probability of early retirement can be caused by the advance of technology in an indirect way. For example, the occupation now is accessible for the incorporation of AI, which makes it more suited for higher educated workers that now have a competitive advantage in this terrain and at the same time, in a terrain where they used to have competitive advantage -collapsing or machine terrain occupations- now they are in a competitive disadvantage situation with new technologies. Finally, higher educated workers can be displaced from collapsing and machine terrain occupations to the rising stars occupations forcing workers without higher education previously in a rising star occupation to early exist the labor market, to obtain higher education, to become self-employed or to move to an occupation in the human terrain.

[12] The Table A2 in the appendix collects some occupations of the human terrain.

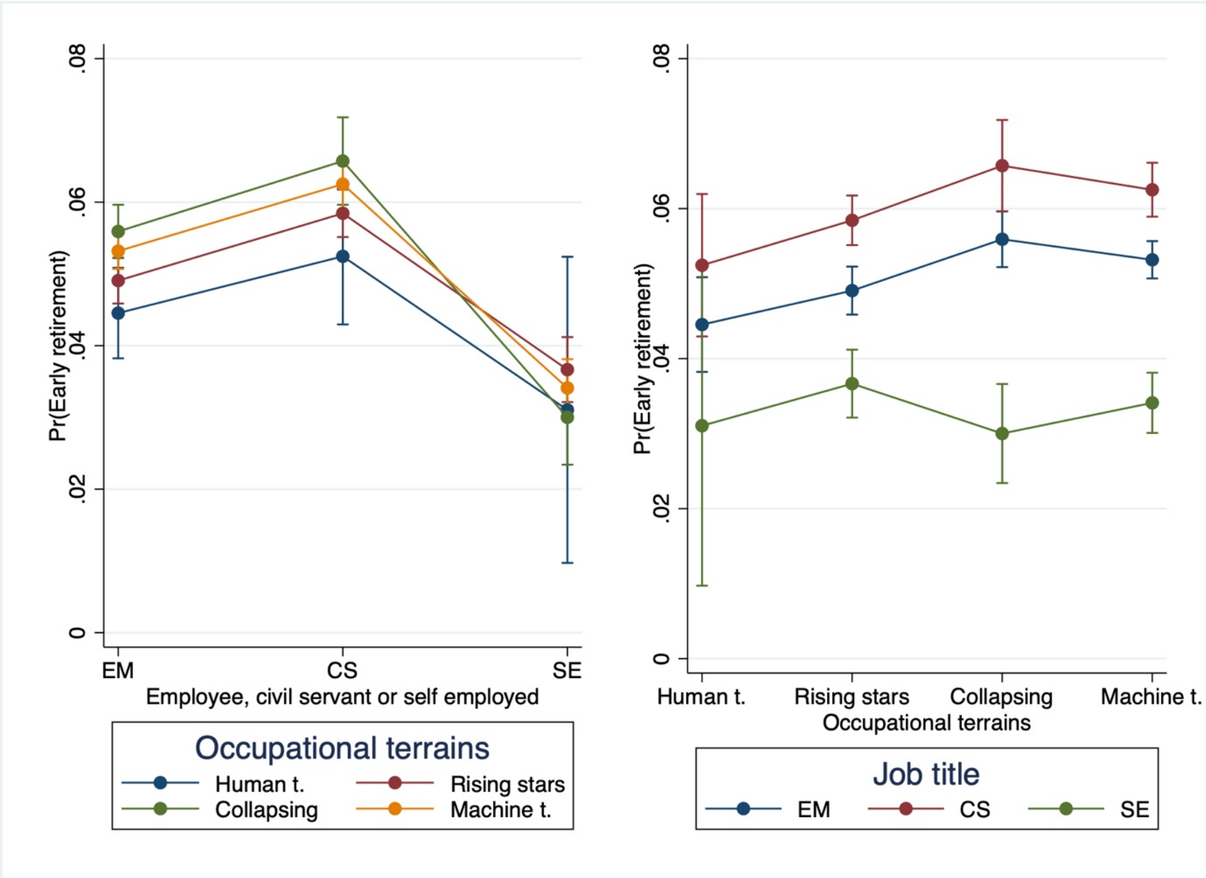


**Figure 5:** Early retirement probability, job status and the occupational terrains
*Note*: Predicted probabilities and marginal effects are from model XII in Table 6.

**Table 11**. Predicted probabilities of early retirement and marginal effects by job status and the occupational terrains.

| | Predicted probability of early retirement | | | Marginal effect of automation risk | | | | | | Marginal effect of job status | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Job status** | EM | CS | SE | EM | | CS | | SE | | EM | CS | | SE | |
| | | | | dy/dx | z-stat | dy/dx | z-stat | dy/dx | z-stat | | dy/dx | z-stat | dy/dx | z-stat |
| **Occupational terrains** | | | | | | | | | | | | | | |
| Human terrain | 0.0445 | 0.0525 | 0.0311 | *Ref.* | | *Ref.* | | *Ref.* | | *Ref.* | 0.0079 | 1.37 | -0.0135 | -1.19 |
| Rising stars | 0.0491 | 0.0584 | 0.0367 | 0.0045 | 1.25 | 0.0060 | 1.18 | 0.0056 | 0.50 | *Ref.* | 0.0094 | 4.04*** | -0.0124 | -4.42*** |
| Collapsing | 0.0559 | 0.0657 | 0.0300 | 0.0114 | 3.10*** | 0.0133 | 2.33** | -0.0010 | -0.09 | *Ref.* | 0.0098 | 2.70*** | -0.0259 | -6.73*** |
| Machine terrain | 0.0532 | 0.0625 | 0.0341 | 0.0086 | 2.50** | 0.0101 | 1.96** | 0.0031 | 0.28 | *Ref.* | 0.0093 | 4.16*** | -0.0191 | -7.98*** |

In the two graphs of Figure 5 and in Table 11 we can observe the relation between the technological classification of occupations and job status regarding the probability of early retirement. Taking the human terrain as the reference group, we observe that employees and civil servants in collapsing occupations or in the machine terrain find their probabilities of early retirement significantly higher. The employees and civil servants with higher early retirement predicted probability are those in the collapsing occupations, followed by those in the machine terrain and those in the rising stars occupations. In turn, the predicted probability of early retirement for self-employed workers does not rely significantly upon the occupational terrain in which they operate. In fact, as we can observe in the left-side graph, while all the lines maintain their orders when connecting employees and civil servants, the lines intersect and the confidence intervals largely intermingle when arriving to the self-employed position. This information is complemented by the center columns of Table 11.

In the right-side graph of Figure 5 and the right-side columns of Table 11 we observe that, taking the employees as the reference groups, civil servants have higher predicted probability of early retirement and self-employed workers lower, in all occupational terrains except for the human terrain. As we may notice, the confidence intervals in the human terrain accounts for a broad set of predicted probabilities of early retirement, being particularly large the confidence interval for self-employed workers.

Interestingly, the widest difference in the probabilities of early retirement between employees (in the public or private sector) occurs in the case of collapsing occupations. In fact, the predicted probability of early retirement for self-employed workers in collapsing occupations is very close (even lower) than the prediction for this collective in the human terrain. These are the lowest predicted probabilities of the intersection: self-employed workers in collapsing occupations and in the human terrain, although we must consider that given the large confidence interval for the case of the human terrain, early retirement probabilities for self-employed workers within this occupational terrain can be much lower even almost reaching the null probability.

The highest predicted probability in the intersection is the one corresponding to civil servants in collapsing occupations, followed by the predicted probability for this job status in the machine terrain. On another note, although for every occupational terrain (leaving aside the exception of the human terrain), we can remark some funny facts: predicted probability for employees in the machine terrain and the collapsing occupations are very close to the ones predicted for civil servants in the human terrain and the rising stars occupations. Therefore, although it still clear that civil servants are more likely to go for early retirement followed by employees and far behind by self-employed workers, the considerations of this technological classification of occupational terrains provide an extra dimension to this analysis.

To summarize, the main message collected by Figure 4 and Table 8 is that self-employed workers have lower predicted probability of early retirement in every occupational terrain and accounting for small variations of the predicted probability when switching occupational terrain, while employees and civil servants account for higher predicted probability in early retirement that can vary broader when switching occupational terrain. Furthermore, the gap in predicted probability of early retirement between two individuals from different job status can be larger or smaller depending on the occupational terrains they belong to.

## 6. Conclusions

Early retirement policies have been around for about 60 years without supposing a big deal for industrialized countries. Nowadays, the ageing of the population combined with a technological change specially aggressive for middle-age workers have made governments to rethink and disincentivize this policies. Nevertheless, few alternative for potential early retirees have been brought into debate.

Eventually, the reason why no alternative policies to early retirement have been proposed is that, traditionally, early retirement has been assumed to be an individual's decision triggered by preferences. However, this study proves that sometimes, to the well-known cases of forced early retirement because of health issues, we must add the consideration of forced early retirement due to technological change.

As we show in the literature review, the consideration of automation as an underlying cause of early retirement has been present in studies since the appearance of these policies although the concrete effect had not been measured until now. Previously, it was better for governments to pay these extra provisions for redundant middle-age workers than slowing down technological change with restrictive labor policies. In fact, the benefits from new technologies for society have been always wider than the cost they bring for some specific groups of population.

However, this approach is very poor in assuming that workers who previously performed work absorbed by new technologies can no longer be valuable to the entire human capital of a country. Although the easy way to solve this issue is to pay generous early retirement or unemployment provisions and look aside, if the wealth generated by new technological change allows it, better policies that does not left anyone behind, can be elaborated, taking full advantage of both technology and human capital, then maximizing the effectiveness of public expenses.

These policies are needed since just delaying retirement ages can simply result in higher unemployment rates, as it has been proved by analyzing the increase of retirement ages in the past. For example, Staubli and Zweimüller (2013) analyze the effects of a gradual increase in the minimum retirement age from 60 to 62.2 years for men and from 55 to 57.2 for women in Austria between 2000 and 2006, to find that this policy change reduced retirement by 19 percentage points among affected men and by 25 percentage points among affected women (this supposed an increase in employment of 7 percentage points among men and 10 percentage points among women), but at the same time, there was an important spillover effect by increasing the unemployment rate 10 percentage points among men and 11 percentage points among women.[13]

Furthermore, as early retirement is logically detrimental for a society due to human capital losses and a descend in economic growth (Conde-Ruiz and Galasso, 2004), it has also been concluded to be detrimental for individuals acceding at this policy. Within this strand of the literature, Börsch-Supan and Schuth (2014) analyze the implications of early retirement for mental health to conclude that cognition declines with early retirement and the effect on well-being appears to be negative and short-lived rather than long-lasting and positive.[14] Palmore et al (1984) analyze the consequences of retirement, by comparing retired and working men, to find that little, if any, differences in health, social activity, life satisfaction, and happiness were caused by retirement, although they found that early retirement had stronger effects than retirement at normal ages. Then, they conclude that retirement has different effects depending on type of outcome and timing of retirement.

Then, according to these studies, early retirement would be a fruitful policy if it achieves to help only individuals taking the decision with total willfulness[15], by promoting solutions so

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[13] On the contrary, Frimmel (2021) also analyzes the case of Austria's reform to conclude that increasing the early retirement age is not only a feasible way to improve the financial sustainability of public pension systems but also improves the re-integration of elderly unemployed male workers.

[14] On the contrary, Litwin (2007) finds that early retirement has no effect on life expectancy.

[15] Isaksson and Johansson (2000) study compared early retirees and persons continuing to work over the years following downsizing with regard to satisfaction, well-being, health, and work centrality, to find that voluntary (as opposed to forced) choice was directly and positively associated with satisfaction, psychological well-being and health for both groups. In this line, Maule *et al.* (1996) study the early retirement decisions of men working in Britain for a large multinational company in the manufacturing sector to indicate that the decision-making process

the forced early retirees can have better alternatives avoiding this involuntary transition. In fact, the cause why opinions are divided regarding the positive (or negative) effects of the decision to go (or not) for early retirement can be explained as a matter of freedom in decision making rather than the decision itself, indicating that the well-being of an individual is greater when he makes the decision he wants and not the one that circumstances force him to make, regardless of the specific decision. Then, from the perspective of welfare maximization, The focus should be on promoting alternative policies that eradicate the possibility of forced early retirement rather than eradicating early retirement in general.

Controlling for demographic characteristics, health level, financial situation, previous employment features and country level variables, we find a positive association between the advance of new technologies – i.e. automation – and early retirement decisions in Europe. Then, we take into consideration the technological mapping of occupations (Fossen and Sorgner, 2019) to find that early retirement probabilities can largely vary depending on the occupational terrain of an individual.

We also find *differentiated effects* depending on education level and job status. On the one hand, regarding the education level, we observe that workers with no higher education and high automation risk are more likely to take the early retirement decision. In addition, individuals with higher education are less likely to retire early independently of the automation risk. On the other hand, regarding the job status, we observe that an increase in the automation risk from low to high is associated with higher probabilities of early retirement for employees in the private sector and civil servants, but not for self-employed workers. As expected, the probability of early retirement for self-employed individuals seems is lower than for employees and civil servants, irrespective of the automation risk.

Regarding the occupational terrains, we find that self-employed, at any occupational terrain, are the individuals with lower early retirement probability while the civil servants in collapsing occupations are the individuals more likely to go for early retirement. Our findings collect that, while being in distinct occupational terrain does not make a difference in the early

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is complex and cannot be reduced to single-factors like health or financial status, and the most important factor in the quality of life of early retirees was the matching of expectations of further work at the point of decision. Smith (2006) points out other relevant difference between voluntary and involuntary early retirees by observing a significant fall in spending only in the latter's.

retirement probability of self-employed, operating in distinct occupational terrains suppose a significance difference in the early retirement probability of employees and civil servants. In addition, getting higher education means a significant descend in the early retirement probability in every occupational terrain. Focusing on individuals without higher education, working in collapsing occupations or in the machine terrain implies significant larger probabilities of early retirement respect to an individual with no higher education in the human terrain. In turn, restricting to the individuals with higher education, only working in a collapsing occupation accounts for higher early retirement probability than working in the human terrain.

In order to take advantage on the accumulated human capital of the middle-aged experienced workers, mechanisms should be established to prevent their early exist from the labor market: (i) to increase spending on training programs for these workers [16] instead of establishing generous early retirement schemes (Fouarge and Schils, 2009) and (ii) to promote bridge self-employment policies for older workers to achieve their statutory retirement age, could be another solution (Axelrad and Tur-Sinai, 2021). For those cases in which the individual at risk of forced early retirement shows no interest on getting higher education or becoming self-employed, it is fundamental that the delay in retirement ages is complemented by other instruments like the mapping of the best routes for the avoidance of early retirement in order to help these middle-age workers at high computerization risk to continue with their working lives. In fact, the same technological wave displacing middle-aged workers can be very useful to their effective relocation as, for example, big data and machine learning, could be the perfect toolkit to design personalized policies. Big data in order to pick up large information about workers' laboral stories, abilities and potential, and machine learning in order to select the best destination for these skills.

[16] In fact, a broader vision would say that increasing the general spending in education can downsize early retirement transitions (and/or its negative effects for an individual) while increasing life quality. Allel *et al.* (2021) find that formal education during childhood and adolescence is associated with a long-term protective effect on health and it attenuates negative health consequences of early retirement transitions. Their results indicate that early retirement is associated with worse health outcomes, but education fully compensates for the detrimental association with subjective and physical health, while adjusting for baseline health, demographics and socio-economic characteristics. Therefore, this research arise the necessity of adopting a broader vision in the elaboration of policies and programs promoting healthy and active ageing would benefit, considering the influence of formal education in shaping older adults' health after the transition into retirement.

## References


[1] Acemoglu, D. and Restrepo, P. 2020. "Robots and Jobs: Evidence from US Labor Markets." *Journal of Political Economy*, 128(6), 2188-2244.

[2] Ahituv, A., and Zeira, J. 2011. Technical progress and early retirement. *The Economic Journal*, *121*(551), 171-193.

[3] Alcover, C. M., Guglielmi, D., Depolo, M., and Mazzetti, G. 2021. "Aging-and-Tech Job Vulnerability": A proposed framework on the dual impact of aging and AI, robotics, and automation among older workers. *Organizational Psychology Review*, *11*(2), 175-201.

[4] Allel, K., León, A. S., Staudinger, U. M., and Calvo, E. 2021. Healthy retirement begins at school: educational differences in the health outcomes of early transitions into retirement. *Ageing and Society*, *41*(1), 137-157.

[5] Angelini, V., Brugiavini, A., and Weber, G. 2009. Ageing and unused capacity in Europe: is there an early retirement trap?. *Economic Policy*, *24*(59), 463-508.

[6] Autor, D. 2015. Why are there still so many jobs? The history and future of workplace automation. *Journal of economic perspectives*, *29*(3), 3-30.

[7] Axelrad, H. 2018. Early retirement and late retirement: Comparative analysis of 20 European countries. *International Journal of Sociology*, *48*(3), 231-250.

[8] Axelrad, H. and Tur-Sinai, A. 2021. "Switching to Self-Employed When Heading for Retirement," *Journal of Applied Gerontology*, 40(1): 95–104.

[9] Barfield, R., and Morgan, J. 1969. Early retirement. *Ann Arbor, Mich.: Institute for Social Research*, 1-6.

[10] Baumann, I., and Madero-Cabib, I. 2021. Retirement trajectories in countries with flexible retirement policies but different welfare regimes. *Journal of aging and social policy*, *33*(2), 138-160.

[11] Bazzoli, G. J. 1985. The early retirement decision: new empirical evidence on the influence of health. *Journal of human resources*, 214-234.

[12] Blekesaune, M., and Solem, P. E. 2005. Working conditions and early retirement: a prospective study of retirement behavior. *Research on Aging*, *27*(1), 3-30.

[13] Blöndal, S., and Scarpetta, S. 1997. Early retirement in OECD countries: the role of social security systems. *OECD Economic studies*, 7-54.

[14] Blundell, R., Meghir, C., and Smith, S. 2002. Pension incentives and the pattern of early retirement. *The Economic Journal*, *112*(478), C153-C170.

[15] Börsch-Supan, A., and Jürges, H. 2009. *5. Early Retirement, Social Security, and Well-Being in Germany* (pp. 173-200). University of Chicago Press.

[16] Börsch-Supan, A., and Schuth, M. 2014. Early retirement, mental health, and social networks. In *Discoveries in the Economics of Aging* (pp. 225-250). University of Chicago Press.

[17] Brugiavini, A, Orso, CE, Genie, MG, Naci, R and Pasini, G. 2019. Combining the retrospective interviews of wave 3 and wave 7: the third release of the SHARE Job Episodes Panel. SHARE Working Papers Series 36–2019.

[18] Celidoni, M., Dal Bianco, C., Rebba, V., and Weber, G. 2020. "Retirement and Healthy Eating," *Fiscal Studies*, 41(1): 199-219.

[19] Comi, S.L., Cottini, E., and Lucifora, C. 2020. "The effect of retirement on social relationships: new evidence from SHARE," *Working Papers del*

*Dipartimento di Economia e Finanza def088*, Università Cattolica del Sacro Cuore, Dipartimenti e Istituti di Scienze Economiche (DISCE).

[20] Conde-Ruiz, J. I., and Galasso, V. 2004. The macroeconomics of early retirement. *Journal of Public Economics*, *88*(9-10), 1849-1869.

[21] Conde-Ruiz, J. I., and Galasso, V. 2003. Early retirement. *Review of Economic Dynamics*, *6*(1), 12-36.

[22] Dorn, D., and Sousa-Poza, A. 2005. Early retirement: Free choice or forced decision?

[23] Dorn, D., and Sousa-Poza, A. 2010. 'Voluntary'and 'involuntary'early retirement: an international analysis. *Applied Economics*, *42*(4), 427-438.

[24] Fossen F., and Sorgner A. 2019. "Mapping the Occupational terrains: Transformative and Destructive Effects of New Digital Technologies on Jobs." *Foresight and STI Governance*, 13(2): 10-18.

[25] Fouarge, D., and Schils, T. 2009. The effect of early retirement incentives on the training participation of older workers. *Labour*, *23*, 85-109.

[26] Frey, C. B., and Osborne, M. A. 2017. "The future of employment: How susceptible are jobs to computerisation?" *Technological Forecasting and Social Change*, 114(2): 254-280.

[27] Frimmel, W. 2021. Later retirement and the labor market re-integration of elderly unemployed workers. *The Journal of the Economics of Ageing*, *19*, 100310.

[28] Grace, K., Salvatier, J., Dafoe, A., Zhang, B. and Evans, O. 2018. "When will AI exceed human performance? Evidence from AI experts." *Journal of Artificial Intelligence Research*, 62: 729-754.

[29] Graetz, G. and Michaels, G. 2018. "Robots at Work." *Review of Economics and Statistics*, 100(5): 753-768.

[30] Hermansen, Å. 2015. Retaining older workers: The effect of phased retirement on delaying early retirement. *Nordic Journal of Social Research*, *6*.

[31] Hernoes, E., Sollie, M., and Strøm, S. 2000. Early retirement and economic incentives. *Scandinavian Journal of Economics*, *102*(3), 481-502.

[32] Hochman, O., and Lewin-Epstein, N. 2013. Determinants of early retirement preferences in Europe: The role of grandparenthood. *International Journal of Comparative Sociology*, *54*(1), 29-47.

[33] Isaksson, K., and Johansson, G. 2000. Adaptation to continued work and early retirement following downsizing: Long-term effects and gender differences. *Journal of occupational and organizational psychology*, *73*(2), 241-256

[34] Jimeno, J.F. 2019. "Fewer babies and more robots: economic growth in a new era of demographic and technological changes," *Journal of the Spanish Economic Association*, 10(2): 93-114.

[35] Litwin, H. 2007. Does early retirement lead to longer life? *Ageing and Society*, *27*, 739.

[36] Manoli, D. S., and Weber, A. 2016. *The effects of the early retirement age on retirement decisions* (No. w22561). National Bureau of Economic Research.

[37] Manyika, J., Chui, M., Miremadi, M., Bughin, J., George, K., Willmott, P. and Dewhurst, M. 2017. *A Future That Works: Automation, Employment and Productivity*. Chicago: McKinsey Global Institute.

[38] Markova, E., and Tosheva, E. 2020. Why to go for early retirement? determinants for early exit from the labour market: the evidence from Bulgaria, *Balkan Social Science Review*, 299-315.

[39] Maule, A. J., Cliff, D. R., and Taylor, R. 1996. Early retirement decisions and how they affect later quality of life. *Ageing and Society*, *16*(2), 177-204.

[40] Nedelkoska, L. and G. Quintini 2018. "Automation, skills use and training", *OECD Social, Employment and Migration Working Papers*, 202.

[41] Palmore, E. B., Fillenbaum, G. G., and George, L. K. 1984. Consequences of retirement. *Journal of gerontology*, *39*(1), 109-116.

[42] Schils, T. 2008. Early retirement in Germany, the Netherlands, and the United Kingdom: A longitudinal analysis of individual factors and institutional regimes. *European sociological review*, *24*(3), 315-329.

[43] Schmidthuber, L., Fechter, C., Schröder, H., and Hess, M. 2021. Active ageing policies and delaying retirement: comparing work-retirement transitions in Austria and Germany. *Journal of International and Comparative Social Policy*, 1-18.

[44] Siegrist, J., Wahrendorf, M., Von Dem Knesebeck, O., Jürges, H., and Börsch-Supan, A. 2007. Quality of work, well-being, and intended early retirement of older employees—baseline results from the SHARE Study. *The European Journal of Public Health*, *17*(1), 62-68.

[45] Smith, S. 2006. The retirement-consumption puzzle and involuntary early retirement: evidence from the british household panel survey. *The Economic Journal*, *116*(510), C130-C148.

[46] Staubli, S., and Zweimüller, J. 2013. Does raising the early retirement age increase employment of older workers?, *Journal of public economics*, *108*, 17-32.

[47] Van Bavel, J., and De Winter, T. 2013. Becoming a grandparent and early retirement in Europe. *European Sociological Review*, *29*(6), 1295-1308.

[48] Wilson, D. M., Errasti-Ibarrondo, B., Low, G., O'Reilly, P., Murphy, F., Fahy, A., and Murphy, J. 2020. Identifying contemporary early retirement factors and strategies to encourage and enable longer working lives: A scoping review. *International journal of older people nursing*, *15*(3), e12313.

[49] Yashiro, N., et al. 2021. "Technology, labour market institutions and early retirement: evidence from Finland", *OECD Economics Department Working Papers*, No. 1659, OECD Publishing, Paris, https://doi.org/10.1787/3ea0c49b-en.

## Appendix

**Table A1**. Descriptive statistics

| | **Total sample** | **Switching to early retirement** | **Non switching to early retirement** | | |
|---|---|---|---|---|---|
| #obs. (#ind.) | 121,026 (17,551) | 6,408 (6,407) | 114,618 (16,980) | | |
| Variable | Mean (S.D. overall) | Mean (S.D. overall) | Mean (S.D. overall) | Min | Max |
| Automation probability (%) | 62.7 (37.6) | 66.3 (36.2) | 62.5 (37.7) | 0.39 | 99 |
| High automation risk | 0.582 | 0.631 | 0.579 | 0 | 1 |
| *Occupational terrains* | | | | | |
| Human terrain | 4.79 | 4.26 | 4.82 | 0 | 1 |
| Rising stars | 37.02 | 32.68 | 37.26 | 0 | 1 |
| Collapsing | 16.94 | 18.15 | 16.87 | 0 | 1 |
| Machine terrain | 41.24 | 44.91 | 41.04 | 0 | 1 |
| Female | 0.511 | 0.480 | 0.513 | 0 | 1 |
| Age | 55.4 (3.58) | 59.2 (3.28) | 55.2 (3.47) | 50 | 66 |
| With partner | 0.803 | 0.808 | 0.802 | 0 | 1 |
| *Health* | 2.9 (1.00) | 3.1 (0.99) | 2.9 (1.00) | 1 | 5 |
| Excellent | 9.5 | 6.37 | 9.67 | 0 | 1 |
| Very good | 22.15 | 17.88 | 22.39 | 0 | 1 |
| Good | 41.39 | 41.92 | 41.36 | 0 | 1 |
| Fair | 22.06 | 26.7 | 21.8 | 0 | 1 |
| Poor | 4.9 | 7.13 | 4.78 | 0 | 1 |
| *Ability to make ends meet* | 2.9 (0.96) | 2.9 (0.95) | 2.9 (0.96) | 1 | 4 |
| With great difficulty | 8.1 | 8.15 | 8.09 | 0 | 1 |
| With some difficulty | 25.76 | 26.9 | 25.69 | 0 | 1 |
| Fairly easily | 31.68 | 32.76 | 31.62 | 0 | 1 |
| Easily | 34.47 | 32.19 | 34.6 | 0 | 1 |
| Tertiary education | 0.301 | 0.233 | 0.304 | 0 | 1 |
| *Job status* | | | | | |
| Employee | 52.69 | 50.61 | 52.8 | 0 | 1 |
| Civil servant | 36.52 | 40.42 | 36.31 | 0 | 1 |
| Self-employed worker | 10.79 | 8.97 | 10.89 | 0 | 1 |
| Full time | 0.87 | 0.90 | 0.87 | 0 | 1 |
| *Sector* | | | | | |
| Primary | 8.08 | 9.22 | 8.02 | 0 | 1 |
| Manufacturing and Construction | 24.23 | 28.56 | 23.99 | 0 | 1 |
| Services | 67.69 | 62.22 | 67.99 | 0 | 1 |
| GDP growth | 1.97 (3.39) | 1.70 (3.56) | 1.98 (3.38) | -14.8 | 11.9 |
| Harmonised unemployment rate | 8.81 (4.39) | 8.80 (4.64) | 8.81 (4.37) | 2.9 | 27.5 |
| Old age pensions pps per capita | 2054.8 (894.8) | 2009.6 (854.8) | 2057.4 (896.9) | 504.68 | 3,929.77 |

**Table A2**: Some occupations in the human terrain

| ISCO-08 Title | ISCO-08 | Comp. Prob. | Advances in AI |
|---|---|---|---|
| Driving instructors | 5165 | .13 | 2.5985351 |
| Other music teachers | 2354 | .13 | 2.5985351 |
| Other arts teachers | 2355 | .13 | 2.9918664 |
| Vehicle cleaners | 9122 | .37 | 1.864328 |
| Actors | 2655 | .37 | 2.8713617 |
| Hand packers | 9321 | .38 | 2.005744 |
| Pelt dressers, tanners and fellmongers | 7535 | .41 | 15.719.488 |
| Sales demonstrators | 5242 | .51 | 29.318.254 |
| Handicraft workers in textile, leather and related materials | 7318 | .52 | 22.117.953 |
| Shoemakers and related workers | 7536 | .52 | 22.117.953 |
| Teachers' aides | 5312 | .56 | 25.386.102 |
| Other artistic and cultural associate professionals | 3435 | .61 | 2.715.867 |
| Fruit, vegeTable and related preservers | 7514 | .61 | 27.546.768 |
| Shelf fillers | 9334 | .64 | 21.545.789 |
| Building caretakers | 5153 | .66 | 20.306.945 |
| Window cleaners | 9123 | .66 | 20.306.945 |
| Domestic cleaners and helpers | 9111 | .69 | 18.491.679 |
| Cleaners and helpers in offices, hotels and other establishments | 9112 | .69 | 20.306.945 |